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A SEGMENTATION SCHEME BASED ON UNIFORM LBP AND MORPHOLOGICAL APPROACH

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Abstract
One of the essential tasks in a wide variety of applications and image processing domains is the need of automatic segmentation. The image segmentation divides an image in to homogeneous regions mainly to locate objects and boundaries such as curves, lines, regions etc. The aim of image segmentation is to extract significant features of image, thus understanding, interpretation, description, analysis of the image scene becomes easy and useful for the machine to perform future tasks. Region segmentation divides images into regions based on pixel intensities, patterns, locations, local shapes and textures or combinations. The region segmentation mainly depends on how effectively the segmentation scheme captures the local attributes. This paper captured the local information by converting the grey level image in to a uniform local binary pattern (ULBP) image. The advantage of this scheme is it only contains the significant information and all non significant local information is represented under a single label. Histogram equalization is used to enhance the local contrast. A morphological treatment is given to this, to smooth the regions and to close narrow gaps between two structures without growing the size of the structures. The Otsu's threshold is used for the final segmentation. The experimental results on four different databases demonstrate the success of the proposed method, compared to many other methods.

Keywords: *Local attributes, Otsu threshold, region segmentation, histogram equalization..*

1. Introduction
One of the most vital objectives of image analysis is image segmentation. This is because the succeeding steps of image analysis such as classification, illustration, description and image understanding and restoration are mainly dependent on segmentation results. The image segmentation plays a critical role in a variety of pattern recognition applications such as robot vision, cartography, inspection of textile products, criminal investigation, remote sensing, object identification and recognition, military surveillance, quality assurance in industries, facial recognition and medical imaging etc. Image segmentation is performed usually using gray level intensities, color, texture, shape or any other feature of interest according to the particular application. The choice of tolerable segmentation idea is essential as it affects the segmentation system. Image segmentation [4, 6, 7, 8] divides an image into different regions depending on various attributes.
There are basically two types of image segmentation methods i) supervised ii) unsupervised. The unsupervised segmentation is more flexible for real world applications. And it is usually more computationally expensive. The problem of image segmentation has established significant concentration in the literature [10], [11], [12][19, 20 , 22 , 21] . There are various segmentation methods base on color of the image and it has wide applications in many areas [13] [14], [15] [16] [17] [20]. Various researchers proposed segmentation methods i.e. based on random field model [3], Pattern trends based on texture units [5], texton patterns to segment retinal vessels [2], three dimensional bi-directional histograms [1]. A segmentation method that is invariant in terms of shape, size, and intensity values is proposed for medical image applications [18]. The accuracy of segmentation is highly dependent on the success or failure of each computerized analysis procedure. A wide-range of research with various integrated methods have been reported in the literature for segmentation, however, still no method is found to be accepted and appropriate for all kinds of images. This

indicates clearly, all segmentation algorithms cannot be equally applicable to a certain application [9]. Recent studies have shown that outstanding texture classification and discrimination can be obtained with local binary patterns (LBP)[23,24,25,26,27]. To capture efficiently the local pattern of texture elements in this paper, we choose local binary pattern (LBP) operator as texture local feature descriptor.
The present paper organized as follows: The section 2 describes the related work. The section 3 and 4 describes the proposed method and results and discussions respectively. The section 5 describes the conclusion.

2. Related work

2.1 Mathematical morphology

Mathematical morphology (MM) is one of the popular non-linear theoretical models for image analysis and processing. Mathematical morphology is referred as a component of natural science and deals with various image components like shape, topology, connectivity etc. The morphological operations are derived from algebraic operators. Morphology is one of the oldest non linear theory and it is examined in 1960 by Matheron and Serra and it is an extension of Minkowski's set theory [28], [29]. Most of the non morphological image processing methods are mostly unsuccessful to find solution for the problems that deal with geometrical variations and aspects of the image. Morphological methods have advantages in dealing with textures due to their nonlinear nature. The morphological transformations retain basic topological properties of objects. Morphology plays a crucial role in segmentation where geometrical properties such as shape, size, connectivity or dissimilarity are considered as feature parameters. There are many morphological operators and many others are derived recently. The interesting thing of morphological operators is all of them are based on two simple operations i.e. dilation and erosion. Morphological operations can be implemented on binary and grey level image. They can also be defined with Euclidean (isotropic) or non-Euclidean (geodesic) metrics.
The morphological operators are very useful for boundary detection, image enhancement, image segmentation, image smoothening, preprocessing, and removal of noise, image understanding and analysis of images. They are widely used and preferred over linear approaches due to their simplicity, efficiency and mainly for direct geometric interpretation.

2.1.1 Gray Value Morphological Processing

The present paper used morphological closing operation on grey level images and grey level morphological operations are described below. The techniques of morphological filtering can be extended to gray-level images. To simplify matters the present study restricted the presentation to structuring elements, Q, that comprise a finite number of pixels and are convex and bounded. However, the structuring element has gray values associated with every coordinate position as does the image A.

The dilation, $D_G()$ in grey level is given by equation 1.

$$D_G(P,Q) = \max_{[j,k]\epsilon\, Q}\{P[m-j, n-K] - Q\,[j,k]\} \quad (1)$$

(1)

The erosion, $E_G()$, is given by the following equation 2.
Erosion

$$E_G(P,Q) = \min_{[j,k]\epsilon\, Q}\{P[m+j, n+K] - Q\,[j,k]\} \quad (2)$$

For a given output coordinate $[m,n]$, the structuring element is summed with a shifted version of the image and the maximum/ minimum encountered over all shifts within the $J\times K$ domain of Q is used as the result of dilation/erosion in grey level morphology.

The images grow and shrink in size by dilation and erosion operators respectively. The quantity, the type and the shape of the image grow or shrink depends upon the structuring element used in these operations. This obviously reflects the truth that morphological operations or processing is dependent on the size, shape and amount of structuring element used. Any morphological operation without a structuring element has no sense i.e. same as low pass filter of an image without specifying the filter.
The morphological grey level opening and closing are defined in equations 3 and 4.

$$\text{Opening} - O_G = D_G\,(E_G\ (P,Q)\ Q) \quad (3)$$

$$\text{Closing} - C_G = E_G\,(D_G\ (P,Q)\ Q) \quad (4)$$

The erosion followed by dilation is called morphological opening. In opening the erosion of an image removes all structures that the structuring element cannot fit inside. Further shrinks all other structures. Then by dilating the result of the erosion with the same structuring element, the structures that are survived by the erosion (were shrunken, not deleted) will be restored. The name tells that the operation can create an opening between two structures that are connected only in a thin bridge without shrinking the structures (as erosion would do). Opening generally smoothes the contour of an object, breaks narrow isthmuses, and eliminates thin protrusions.
The dilation followed by erosion is called closing. The morphological dilation of an image expands the object and fills small gaps. By eroding this image will retain their structure and form, without any change, but tiny holes filled by dilation will disappear. Images merged by the dilation will not be separated again. The image will be smoothed by closing. This smoothening

usually mingles thin breaks and long thin gulfs. This removes or eliminates minute holes, and fills gaps in the contour. This retains the uniformity of a local region.

The advantage of grey level morphology is it reduces significantly the overall complexity of processing by the use of symmetric structuring elements. The definitions of above are reduced to the following equations 5, 6, 7 and 8.

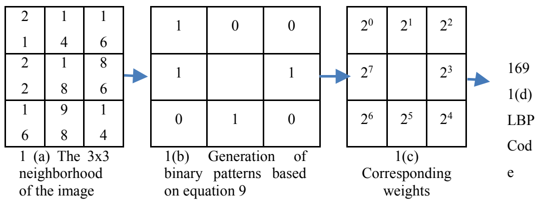

Figure 1: Local binary patten approach.

$$\mathit{Dilation} - D_G(P,Q) = \max_{[j,k]\in Q}\{P[m-j,n-k]\} = \max_Q(P) \quad (5)$$

$$\mathit{Erosion} - E_G(P,Q) = \min_{[j,k]\in Q}\{P[m-j,n-k]\} = \min_Q(P) \quad (6)$$

$$\mathit{Opening} - O_G(P,Q) = \max_Q\left(\min_Q(P)\right) \quad (7)$$

$$\mathit{Opening} - O_G(P,Q) = \min_Q\left(\max_Q(P)\right) \quad (8)$$

The noteworthy conclusion from this the maximum and the minimum filter are exactly same as dilation and erosion in grey level respectively. In this case the shape of the filter window will become the specific structuring element. For a window of size J×K, the maximum or minimum filter is separable into two, one-dimensional windows. Further one can compute easily in incremental form, a one-dimensional maximum or minimum filter. This means the computational complexity per pixel of dilation or erosion is O(constant). Thus these morphological operations and also all other operations of morphology are independent of J and K.

2.2. Local binary pattern

The Local binary pattern (LBP) was introduced by Ojala et al. [30] in 1996. The LBP operator converts the grey levels of an image into integer codes called as LBP codes. The LBP code describes the local patterns, attributes and properties very significantly. The process of evaluating LBP codes are shown in Figure 1. Initially the neighborhood pixels are converted in to binary by computing the grey level differences between the central pixel and the corresponding neighborhood pixels based on as given in equation 9. Then the binary values of the neighbors are multiplied with the corresponding weights. Summation of these gives a LBP code for the window and the central pixel value is replaced with the derived LBP code as given in equation 10.

$$b_i = S(P_c - P_i) \quad i=0 \text{ to } 7 \quad (9)$$

$$\text{where } b_i = \begin{cases} 1 & S(x) \geq 0 \\ 0 & S(x) < 0 \end{cases}$$

$$lc = \sum_{i=0}^{7} b_i * 2^i \quad (10)$$

where P_c, P_i represents the gray values of central pixel and neighborhood pixel i, b_i represents the binary value of the corresponding neighboring pixel. lc represents the LBP code for the 3x3 window. The transformation process of LBP code is also shown in the Figure 1.

In literature uniform LBPs (ULBP) are derived on binary LBP. The ULBPs are considered as most important properties of image texture. More than 85 % of image windows will have ULBP's. The remaining windows are treated as Non-uniform LBP's (NULBP). The LBP codes are defined as uniform if they contain at most two circularly bitwise transitions from 0 to 1 or vice versa, and non-uniform patterns if otherwise [31]. While mapping a LBP image into ULBP image, unique code is used for each ULBP and all non-uniform patterns are accumulated with a single code and treating them as miscellaneous. Most LBPs in natural images, textures and human faces are uniform patterns [31, 32]. A 3 x 3 neighborhood with 8-neighbors derives 256 ($2^{P)}$ LBP codes, whereas by transforming this in to ULBP codes the number of codes will be reduced from 2^P to P(P-1)+3. Here P represents the number of neighboring pixels. The present paper established, the advantage of considering ULBP's because it retains the basic fundamental properties of the image, which is very useful for segmentation purpose and it greatly reduces the image dimension.

2.3. Thresholding by Otsu method

One of the crucial steps in image processing is thresholding. Thresholding divides the image in to two or more regions based on the threshold levels. That's why thresholding is one of the crucial and significant steps in image segmentation. A threshold can be used to segment the image in the following way.

If G (x, y) > T then G (x, y) = 0 else G (x, y) = 1 or maximum intensity.

where G (x, y) represents the grey level intensity of the pixel at co-ordinate position x, y. T represents the threshold chosen randomly or by any other methods. To make segmentation more accurate and robust, the threshold should be selected automatically. Threshold is selected based on the familiarity and knowledge about the images and the application and also based on

intensity characteristics of the objects, sizes of the objects, fractions of an image occupied by the objects, number of different types of objects appearing in an image colour combination etc.

The Otsu method, as proposed by [33] is based on discriminate analysis. Otsu's method chooses the threshold by minimizing the within-class variance of the two groups of pixels separated by the thresholding operator. A measure of region homogeneity is variance (The regions with high homogeneity will have low variance). The advantage of Otsu threshold is it does not depend on modeling the probability density functions.

The Otsu threshold is based on a bimodal distribution (foreground pixels and background pixels) of gray-level values. The Otsu threshold operation performs the division of image pixels into two classes C0 and C1 (e.g., objects and background) at gray level t, i.e., C0 = {0, 1, 2, t} and C1 = {t + 1, t +2….L-1}.

Let σ^2B, σ^2w and σ^2T be the between-class variance, within-class variance and the total variance, respectively. An optimal threshold is determined in the Otsu method by minimizing one of the following criterion functions with respect to:

$$\lambda = \frac{\sigma_B^2}{\sigma_W^2}, \eta = \frac{\sigma_B^2}{\sigma_T^2}, \kappa = \frac{\sigma_T^2}{\sigma_W^2} \tag{11}$$

The optimal threshold't' is defined as

$$t = \text{ArgMin } \eta \tag{12}$$

$$\sigma_T^2 = \sum_{i=0}^{L-1}[1-\mu_T]^2 \, P_i, \;\; \mu_T = \sum_{i=0}^{L-1}[iP_i] \tag{13}$$

$$\sigma_B^2 = w_0 w_1 (\mu_0 \mu_1)^2 \tag{14}$$

$$w_0 = \sum_{i=0}^{t} P_i, \;\; w_1 = 1 - w_0 \tag{15}$$

$$\mu_1 = \frac{\mu_T - \mu_t}{1-\mu_0}, \mu_1 = \frac{\mu_t}{W_0}, \mu_t = \sum_{i=0}^{t}(iP_i) \tag{16}$$

$$n = \sum_{i=0}^{L-1} n_i \tag{17}$$

$$P_i = \frac{n_i}{n}$$

Where n_i is the number of pixels with gray-level ' i ' and ' n ' denotes spatial resolution of the given image. Moreover, P_i is the probability of occurrence of gray level ' i '.

The class probabilities w_0 and w_1 specify parts of the areas engaged by classes C_0 and C_1 for a chosen threshold 't' . The approximation s of mean levels of the classes of original image is provided by class means μ_0 and μ_1. The η^* represents the obtained maximum value of η. The η^* is used to compute the separability of classes C_0 and C_1 in the original or the bimodality of the histogram. This is crucial measure. It is uniquely determined within the range $0 \leq \eta \leq 1$. If and only if a given image shows a single constant gray level, then the lower bound (zero) is obtained. And the upper bound (unity) is achieved if and only if two-valued images are given. The proposed method used Otsu thresholding scheme to properly establish boundaries without noise and falling edge problems.

3. Methodology: Morphological Uniform LBP (MULBP) Segmentation Method

The proposed MULBP segmentation method divides the entire process into five steps. The first step converts the colour image into grey level image using RGB colour model. To represent effectively the local attributes of the image LBP is applied on the image. The image is encoded with Uniform LBP codes (0 to 59). Histogram equalization is applied to amplify the grey levels of ULBP coded image. This in fact enhances the local grey levels. Then morphological closing operation is applied to treat the uniform local regions. Finally Otsu threshold is applied to obtain segmented image. The proposed MULBP segmentation is a novel method because it achieves a good segmentation with five steps and thus it is more suitable to real time applications. The block diagram of proposed MULBP method is given in Figure 2.

STEP 1: Converts the colour image in to grey level image, by using RGB colour model.

STEP 2: To establish local features on a 3 x 3 neighborhood, the grey level image is converted in to LBP coded image. If the neighborhood forms a NULBP window then its central pixel is replaced with the miscellaneous code 59. The ULBP codes are quantized from 0 to 58. The formation of LBP codes and ULBP is given in section 2.2.

STEP 3: The histogram equalization (HE) is derived on the ULBP image of step 2, to identify interior details and to enhance the contrast of the image.

STEP 4: On the histogram equalized ULBP image, the morphological closing is applied to derive the uniform local regions of the image. Closing connects the objects that are close to each other. That is the closing fills up small gaps and smoothes the outline of the object. The morphological operations are described in section 2.1.

Step 5: To establish boundaries in the image, Otsu thresholding is performed on the image obtained in step 4 as explained in section 2.3.

The proposed MULBP evaluated the performance of the segmentation scheme by deriving various statistical measures on segmented images. One of the popular methods to evaluate the performance of the segmentation method is by subjective evaluation. In this a human visually approximates by comparing the segmentation results with various other segmentation approaches. The supervised evaluation is the other method for assessment. In this segmented output, will be compared with the original image. Both the above assessment methods need interaction of the user, that's why they are impractical in several computer vision tasks. Therefore to identify the performance of the segmentation process "unsupervised approaches" [34, 35] are required. The comparison with ground truth or original images is not required in unsupervised

estimation methods, thus it takes less time in evaluating the performance of the segmentation method. That's why these estimation methods are popular and preferred in real time and other applications.

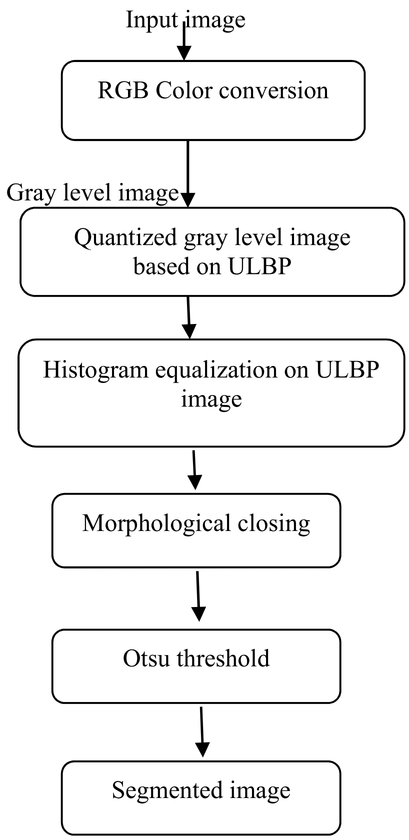

Figure 2: Block diagram of the proposed MULBP method.

The present paper considered the following popular and widely referred segmentation metrics i.e. standard deviation, contrast, discrepancy and entropy. Discrepancy is given as

$$Discrepancy = \sum_{i}^{I_h}\sum_{j}^{I_w}\left(\mathrm{X}_{gl}(i,j) - \mathrm{Y}(i,j)\right) \quad (18)$$

Where $X_{gl}(l, m)$ and $Y(l, m)$ represents the gray level values at pixel co-ordinates l, m of the original and final image. If the value of discrepancy is high, then it indicates a better segmentation.

Entropy of an image is given as

$$Entropy = -\sum_{i}\sum_{j}\mathrm{S}(i,j)log\left(\mathrm{S}(i,j)\right) \quad (19)$$

Over segmentation and under segmentation can be assessed with entropy values. An entropy value less than 1 and above 1.5 represents over segmentation and under segmentation respectively.

Standard deviation of a given vector is expressed as

$$\mathrm{S} = \left[\frac{1}{\mathrm{n}-1}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{x_i} - \bar{\mathrm{x}})^2\right]^{\frac{1}{2}} \quad (20)$$

Where x_i and $\bar{x}$ are the value of vector and average of all values.

A better segmentation is estimated with lower values of standard deviation. Internal region contrast is defined as

$$\mathrm{I_j} = \frac{1}{\mathrm{S_j}}\sum_{\mathrm{s}\in\mathrm{R_j}}\max\left\{\mathrm{c(a,b), b \in W(a) \cap R_j}\right\} \quad (21)$$

Where neighborhood is denoted by W(a), and c(a, b) = $|C_x(a) - C_x(b)|$ is the contrast of pixel 'a' and 'b'. The region uniformity is measured by internal contrast, I_j. The I_j represents "region average Max Contrast". Uniformity is one of the important attributes of the segmentation. A good segmentation method should divide the image without disturbing the region uniformity. A high uniformity is measured with a low value of internal contrast.

4. Results and discussions

The proposed MULBP segmentation method is tested on four large databases namely WANG [39], OXFORD flowers [40], INDIAN facial expressions [41] and standard images from Google (Lena, Camera man, House, Mandrill, and Ship). We have tested the MULBP segmentation method on 150 images from each of the above data bases and this result to a total of 4 x 150=600 different images.

The WANG database consists of 1,000 natural images. These images are manually selected from the famous Corel stock photo database. The WANG database divided these 1000 images in to 10 classes and each class contains 100 images. This database is selected because mostly these images are used for image retrieval and classification experiments. The good segmentation of these images will have further applications in retrieval and classification. The OXFORD flower database consists of flowers of 17 categories. The flower images are most suitable for segmentation experiments' because they contain sharp edges with different shapes and different local attributes. In each category there are 80 images. This results to a total of 17 x 80= 1360 images. The segmentation plays a crucial role in facial image recognition, image retrieval, facial expression identification, ageing problems and age classification. That's why the present paper chosen Indian data base that contains facial images. These images are taken at IIT Kanpur campus and placed in the web in February 2002. This set consists of 59 different classes and each of this contains 11 different facial images (59 * 11 = 649 Images). Some additional photographs are included in some classes. On a bright homogeneous background these images are captured. The resolution of images is 640x480 pixels, with 256 grey levels per pixel. The facial images contains both genders male and female), with different age groups, with different expressions (neutral, smile, laughter, sad/disgust) and emotions.

To show the step wise performance, the proposed MULBP is applied on eight input images from the above data bases and results are shown in Figure 3, and they clearly establish the following facts.

1. The ULBP captured local information significantly.
2. The contrast of the local ULBP regions is enhanced by histogram equalization.
3. The proposed morphological treatment filled the small holes and established uniform local regions for a better segmentation.
4. The Otsu threshold established local boundaries of the image effectively and also removed unwanted non significant portions of the image.

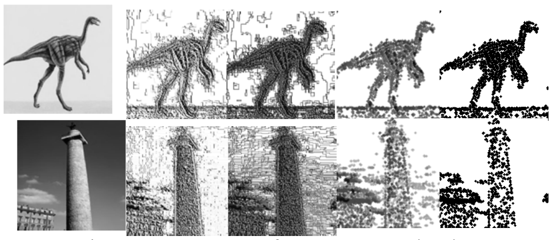

Figure 3.1: Images from WANG database.

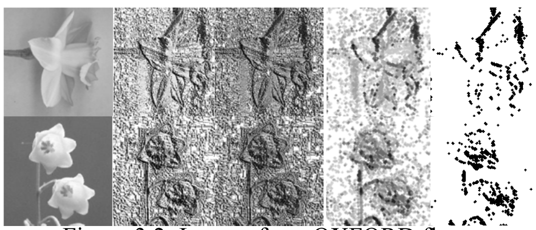

Figure 3.2: Images from OXFORD flower database

Figure 3.3: Images from INDIAN database.

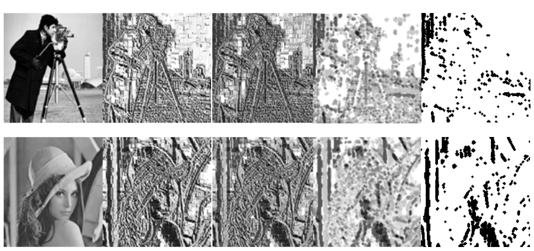

Figure 3.4: Images from Google database.

(a) (b) (c) (d) (e)

Figure 3: (a) the gray scale images (b) ULBP images of (a) (c) Histogram equalization outputs of (b) (d) Output images after closing operation (e) the MULBP segmented images.

The present paper evaluated the discrepancy, standard deviation, entropy and contrast values on the 600 segmented images (150 from each database) on the proposed MULBP and other existing segmentation methods i.e. ISLGHEM [36], automatic threshold method [37] and wavelet based watershed method [38]. The average value of 150 images from each database is plotted in the form of bar graphs in Figure 4, Figure 5, Figure 6 and Figure 7.

The graphs clearly indicate the higher discrepancy value and a lower value of the standard deviation for the MULBP method over the other methods. This reflects a better segmentation of the proposed over the existing methods. The low value of internal contrast of MULBP represents a high uniformity in the region. A segmentation mechanism may lead into over and under segmentation. An under segmentation will be resulted if there are too few regions where as too many regions leads to over segmentation. A over segmentation is a undesirable characteristic. The over segmentation problem is overcome by the proposed method and it is reflected in the form of entropy value.

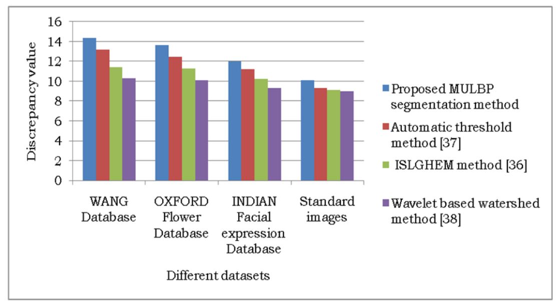

Figure 4: Discrepancy graph of various segmentation schemas on considered databases.

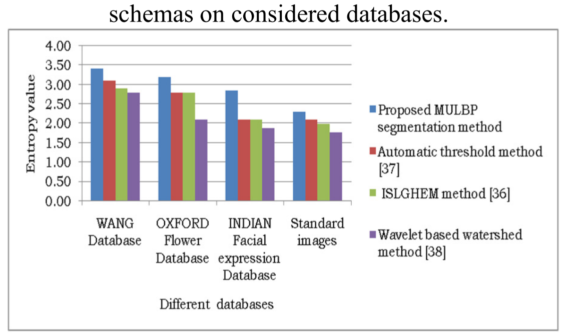

Figure 5: The entropy graph on segmentation methods using different databases.

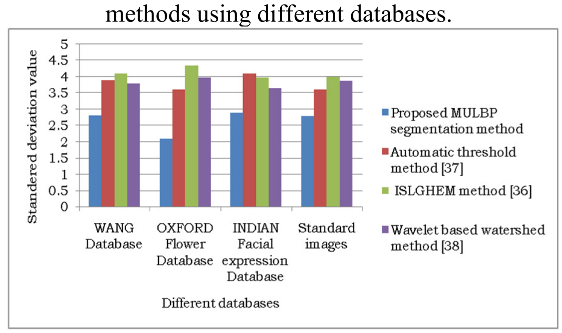

Figure 6: The standard deviation graph on segmentation methods using different databases.

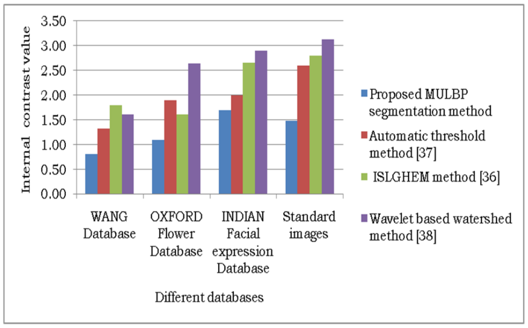

Figure 7: The internal region contrast graph on segmentation methods using different databases.

5. Conclusions

The MULBP identified local attributes efficiently by the usage of the powerful, simple and robust local operator i.e LBP. The other significant advantage of considering ULBP is it is rotationally invariant because the ULBP is measured on circular bit pattern of a 3 x 3 neighbourhood. The morphological treatment filled the small holes and connected borders of regions for a better segmentation. The Otsu threshold established local boundaries efficiently and provided better contrast and also removed the unwanted local scenes of the image. The whole process of segmentation is autonomous and requires no supervision. The MULBP segmentation improves the contrast of sharp details in light and dark areas because of LBP-window based property and it showed higher performance when compared other three methods of segmentation. The present method is simple and suitable to real time applications because it achieved good segmentation with five basic steps.

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